DEVELOPMENT OF CUSTOMER DECISION MODEL IN SELECTING PRODUCT CONCEPT BASED ON *CONJOINT-ANALYSIS-LIKE AHP* (*CALAHP*)

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Keyword: customer preference model, AHP, conjoint analysis, CALAHP, new product development

Summary: *Business competition becomes progressively severe in the era of globalization. Changes become faster and faster. Customer's wants and needs keep changing continuously. It is a challenge for companies to improve their existing products and develop the new ones. Therefore, a company has to be able to develop new products conforming customer preferences in a relatively short time.*

Customer requirements cannot be expressed in an explicit way since they are influenced by customer's perceptions and preferences of a certain product. Some methods have been developed to measure customer's preferences. Two methods that are commonly used are conjoint analysis and Analytic Hierarchy Process (AHP).

AHP is generally used by decision makers to maximize subjective utility in decision analysis, while conjoint analysis is generally used to maximize customer preferences in marketing, especially for the product development. Each of those methods has strengths and weaknesses, compared to each other, that are: (i) Conjoint analyisis has an ability to predict the score of product concepts which are not evaluated directly, while AHP can predict only those which are evaluated directly; (ii) AHP can be used to evaluate product concepts with sub-attribute, while conjoint analysis cannot evaluate product concepts with sub-attribute; (iii) Scores of alternatives produced by AHP are more dispersed compared to conjoint analysis. In addition, AHP and conjoint analysis can only facilitate problems with finite alternatives, while product development demands method which can facilitate problems with infinite alternatives (i.e. attribute's level with continuous value).

This research has developed derivative model of AHP in order to improve AHP so that it has the ability of conjoint analysis (conjoint-analysis-like AHP) and to facilitate the representation of alternatives with continuous attribute value. The examination of the results indicates that the developed model is more sensitive than AHP and has a better predictive ability than conjoint analysis. This research has also indicated that further research can be conducted, for example by considering uncertainty factor and by involving statistical analysis.

Key Words: model, CALAHP, AHP, conjoint analysis, product development

1. Introduction

A new products will be accepted by the market if only consumer sees that it represents a solution for their requirements or needs. Therefore, a company has to be able to develop its new products according to their customer preferences. Because the product life cycle becomes shorter and shorter, this new product development process should be accomplished in a short time.

The measurement of consumer preferences, which is conducted at the early stage of product development process, helps the company in predicting market share of particular product concept alternative(s) and then decreasing the risk of new product failure. The measurement of consumer preferences becomes a main issue for some research areas, such as marketing and decision analysis (Helm et.al., 2004). According to Yudhistira (2002), there are two methods that are commonly used for the measurement, i.e *Conjoint Analysis* and *Analytic Hierarchy Process (AHP)*

Table 1 Preference measurement in decision analysis and marketing

	Decision Analysis	Marketing
Problem	Selection of alternatives	Design of products/services
Objective	Maximum subjective utility	Maximum consumer preferences
Core problem	Modeling and measuring preferences	Modeling and measuring preferences
Selection methods	Scoring methods Multi-attribute utility theory Analytic Hierarchy Process (AHP)	Self explanatory methods Multidimensional scaling Conjoint Analysis (CA)

Source: Helm, et.al.(2004)

Decision analysis and marketing actually have the same core problem (see Table 1), that is modeling and measuring preferences. Therefore, the selection methods used in each area are comparable to one another. Both methods have its strength and weaknesses. Some comparisons of both methods are as follows (Yudhistira, 2004):

- Conjoint Analysis has an ability to predict the consumer preference value on product concepts that are not evaluated directly, while AHP can only predict those that are evaluated directly.
- AHP can be used to evaluate product concepts with sub-attribute, while conjoint analysis cannot evaluate product concepts with sub-attribute.
- Scores of alternatives produced by AHP are more dispersed compared to those produced by Conjoint Analysis.
- Scores of alternatives produced by AHP are deterministic and *a priori*, while scores produced by Conjoint Analysis must be interpreted statistically.
- Both AHP and conjoint analysis can only facilitate problems with finite alternatives, while actual product development process demands method that can facilitate problems with infinite alternatives (i.e. attribute level with continuous value) because attributes are usually described as numeric variables.

2. Conjoint Analysis Basic Concepts

Conjoint analysis is a multivariate technique used specifically to understand how respondents develop preferences for products or services. It is based on the simple premise that customers evaluate the value of a product/service/idea (real or hypotethical) by combining the separate amounts of value provided by each attribute (Hair et.al., 1999).

The term ***factor*** is used to describe a specific attribute or other characteristic of the product or service. The possible values for each factors are called ***levels***. In conjoint terms, a product or service is described by its level on the set of factors characterizing it. When the researcher selects the factors and the levels to describe a product or service according to a specific plan, the combination is known as a ***treatment*** or ***stimulus***.

Basic model of conjoint analysis can be expressed as follow:

$$Y_1 = X_1 + X_2 + X_3 + ... + X_n \quad (1)$$

where Y is a nonmetric or metric variable and X is a nonmetric variable.

Utility function in conjoint analysis is composed by the utility scores of each product's attribute. If m is an index for a profile (stimulus), then for each customer on the sample, the preference score P_m for the product's profile m is given by

$$P_m = u_1(y_1) + u_2(y_2) + ... + u_n(y_n) + C \tag{2}$$

where u_i = utility function for attribute i or weight for attribute i
y_i = score of attribute's level i

3. Model Development

The model developed is expected to satisfy following requirements:

- It provides a convenience way for respondents to evaluate the profiles by not presenting many items to be evaluated.
- It can rank all possible product concept alternatives.
- It considers the relationship between one attribute and another (non additive assumption).
- It accommodates sub-attributes.
- It can estimate the score of an attribute's level which is not evaluated directly.

The developed model is called *conjoint-analysis-like AHP (CALAHP)*. Its hierarchy structure is shown on Figure 1.

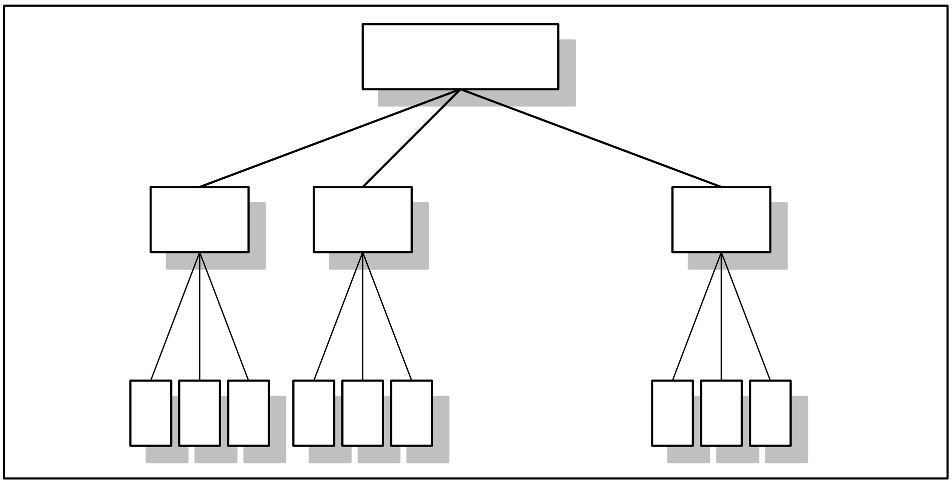

Figure 1 Hierarchy structure on AHP developed model.

The steps in *CALAHP* are described completely as follows:

1. Attribute Levels Scoring

   Scoring of attribute's level is done according to regular AHP and followed by the dividing-by-maximum-value normalization (Zeleny, 1982).

$$\hat{a}(x_i)_j = \frac{a(x_i)_j}{\max(a(x_i)_j)}, \forall i, j \tag{3}$$

   where i, j are subscript for levels.

   Mean of the normalized scores then becomes the final score of the attribute's level.

$$A(x_i) = \frac{\sum_j \hat{a}(x_i)_j}{n} \tag{4}$$

   where n is the number of columns (attribute's levels). All of the values a_{ij} have to be consistent.

2. Determining the utility function of attribute's level

The definition of utility function makes model could estimate the value of attribute's levels that are not directly determined, so that the model can accomodate continuous-valued-attribute-levels problems (attributes which levels are represented by real numbers).

There are several methods in smoothing the sample points in order to obtain the function. In this research, Lagrange interpolation is chosen because it provides zero error and it is easy to be implemented in various situation.

A set of samples is given below:

$$\langle x_1, A(x_i)\rangle, \langle x_2, A(x_2)\rangle, ..., \langle x_n, A(x_n)\rangle$$

where x_i represents levels value (real numbers) and $A(x_i)$ is its corresponding score. For simplification, $A(x_i)$ will be written as y_i. Function f which interpolates the sample given above for all $x \in R$ is written as follows:

$$f(x) = y_1 L_1 + y_2 L_2 + ... + y_n L_n \quad (5)$$

where $$L_i(x) = \prod_{\substack{k=1 \\ k \neq i}}^{n} \frac{x - x_k}{x_i - x_k} \quad (6)$$

for $i \in N_n$.

3. Determining attribute's weight

CALAHP uses two kinds of weight, *a priori* and informational weights (Zeleny, 1982). Informational weight is used to accomodate the relationship between atribute level scores and attribute weight and to accommodate the situation with interdependencies of one attribute to an other (non additive assumption).

These following steps are employed to obtain *a priori* weight used in CALAHP:

(1) Derivation of *a priori* weight

The *a priori weight* is derived using AHP, i.e using the pairwise comparison.

(2) Normalization

CALAHP refers to Zeleny (1982) which divides the value of the weight by the maximum value of the column corresponds to the value. With this kind of normalization, CALAHP would be more thorough in concerning a small difference.

$$\hat{w}_{ij} = \frac{w_{ij}}{\max(w_{ij})}, \forall i, j \quad (7)$$

(3) *A priori* weight calculation

the value of *a priori* weight is equal to the mean of the normalization

$$W_i = \frac{\sum_j \hat{w}_{ij}}{n} \quad (8)$$

The information weight is calculated as follows:

(1) Calculate the amount of all normalized attribute level score for each attribute.

$$D_i = \sum_j \hat{a}_{ij}, \forall i \quad (9)$$

where d_{ij} = value of attribute's level j in attribute i

(2) Calculate

$$K = \frac{1}{\ln n} \tag{10}$$

where n = number of attributes.

(3) Then calculate

$$e(d_i) = -K\sum_{j=1}^{m}\frac{\hat{a}_{ij}}{D_i}\ln\frac{\hat{a}_{ij}}{D_i} \qquad \text{for } i = 1,2,....,n \tag{11}$$

where m = number of level(s) in attribute i
n = number of attribute(s).

(4) Calculate

$$E = \sum_{i=1}^{n} e(d_i) \tag{12}$$

where n = number of attribute(s).

(5) Calculate informational weight as follows:

$$\tilde{\lambda}_i = \frac{1}{n-E}[1-e(d_i)], \forall i \tag{13}$$

where n = number of attribute(s).

Calculation of total weight is conducted by multiplying the two kinds of weights obtained above.

$$\lambda_i = W_i \times \tilde{\lambda}_i \ ; \qquad \text{for } i = 1, 2, ..., n \tag{14}$$

Then it is normalized by dividing each λ_i by the maximum value of the weights. So, we will obtain a total weight for each attribute.

$$\lambda_i' = \frac{\lambda_i}{\max\limits_i(\lambda_i)} \tag{15}$$

4. Determining preferences score

Preference score for each stimulus/profile is calculated by multiplying the value of attribute level corresponds to the profile with total weight of the attribute corresponds to the attribute level.

$$V(A_i, B_j, ..., N_n) = \lambda_A'.A_{A_i} + \lambda_B'.A_{B_j} + ... + \lambda_C'.A_{N_n} \tag{16}$$

where $V(A_i, B_j, ..., N_n)$ = score of preference of a profile with combination of attribute level $A_i, B_j, ..., N_n$
λ_A' = total weight of attribute A
A_{A_i} = value of attribute level i in attribute A

5. Aggregation

Aggregate attribute level score is calculated using geometric mean of the values in pairwise comparison.

$$\bar{a}_{ij} = (z_1 \cdot z_2 \cdot .... \cdot z_n)^{1/n} \tag{17}$$

where $\bar{a}_{ij}$ = aggregate score
z_i = value of a_{ij} given by respondent i
n = number of respondents.

While aggregation of attribute's weight is conducted by calculating arithmetic mean of the values of weights given by each respondent.

$$\overline{w}_i = \frac{\sum_{k=1}^{n} z_k}{n} \quad (18)$$

where $\overline{w}_i$ = aggregated weight for attribute i
z_k = weight for attribute i given by respondent k
n = number of respondent(s).

6. Ranking

   Ranking is conducted by sorting each profiles by its preference score descendingly.

4. Model Implementation and Analysis

Hereby, it is presented an example of model implementation by using a case study the selection of notebook computer product concept alternatives. Notebook computer attributes considered in this case study are shown in Table 2.

Table 2. List of level's atrribute of notebook.

Attribute	Level
Screen diagonal	10 inches, 12 inches, 14 inches, 15 inches, 17 inches
Processor	1.5 GHz, 1.8 GHz, 2.1 GHz, 2.4 GHz, 3.0 GHz
Battery endurance	3 hours, 5 hours, 7 hours, 9 hours
Price	US$ 1,200, US$ 1,500, US$ 1,900, US$ 2,100, US$ 2,500

Evaluation using questionnaires were given by ten respondents who are users of notebook. To compare performance of the developed model to conjoint analysis, 25 stimuli and six holdout stimuli were generated using *SPSS*. These 25 stimuli were then presented to the respondents to be evaluated using rating system (scale 1 to 7) and using ranking system for the holdouts. This ranks then were compared to the ranks produced by CALAHP.

Then, from the responses, using Lagrange interpolation we got the function for scoring attributes. For example, for processor attribute levels, the function was:

$$f(x) = 0.1145\, L_1(x) + 0.17789\, L_2(x) + 0.34029\, L_3(x) + 0.59145\, L_4(x) + 1\, L_5(x)$$

Using this function, we can predict the score of attribute's levels that are not directly evaluated, such as 2.0 GHz or 2.8 GHz. The graphical representation of the function is shown in Figure 2.

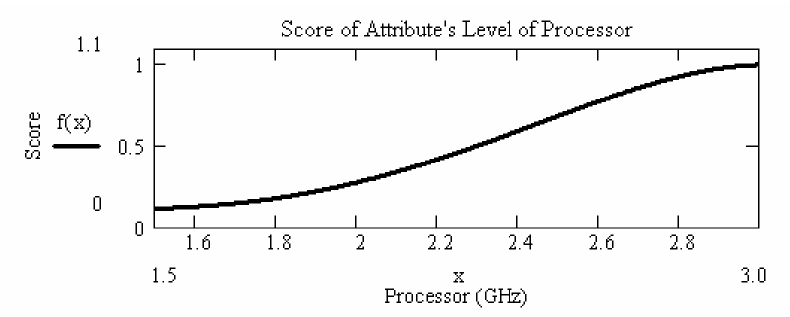

Figure 2 Graphical representation of aggregate attribute's level score of processor function

Table 3. *Face validity* of respondents answer.

Attributes	*CALAHP*	Conjoint Analysis
Processor	1	0.3
Battery endurance	1	0.4
Price	1	0,3

From Table 3 we can see that CALAHP's face validity is better than Conjoin Analysis's. CALAHP is better because it has internal validation procedure and the attribute level evaluation is done separatedly for each attribute, with an assumption that relationship between attributes is explained by informational weight. On the other hand, conjoint analysis evaluates an attribute's level in relation with other attribute's levels so that the score of an attribute's level would depend on the score of other attribute's levels in the evaluated stimuli.

To assess model's ability in predicting customer preferences, we can use hit-rate method (Helm, et.al., 2004) which count the percentage of matching ranks frequencies from two different methods. In addition to hit-rate method, we also employed NAC (*number of agreement and conflict*) value developed by Ray and Triantaphyllou (1998) to calculate the percentage of agreement number compared to the number of all decisions. One agreement is achieved when elements in the rank *i* for the two ranks are the same. In this case study, CALAHP has an NAC = 0,58 while conjoint analysis has an NAC = 0,55.

Table 4 *Hit-rate* of aggregate results and direct evaluation.

Hit Rate	CALAHP	Conjoint Analysis
HR1	0.5	0.5
HR12	0.5	0.5
HR123	0.3	0.1
HR{12}	0.6	0.6
HR{123}	0.4	0.4

The predictive ability of CALAHP is supported by the consistency measurement using internal validity. This measurement is not applicabble in conjoint analysis, resulting in the greater possibility of occuring number crunching. Beside that, CALAHP has a direct subjective evaluation in determining *a priori* weights, making respondents intervention becomes possible. On other hand, prediction ability of conjoint analysis is supported by the similarity of its alternative presentation with the presentation of holdout stimulus which are evaluated directly, so that respondents could answer consistently.

To observe how CALAHP works in different situations, an experiment using hypothetical data is conducted. Those different situations are developed in scenarios.

4.1 Scenario 1

A decision model must be able to recognize a nondominated solution/alternative, if it exists (Yudhistira & Diawati, 2000). Scenario 1 tests the model ability in recognizing the nondominated solution.

Table 5. Evaluation data for scenario 1.

Attribute	Weight	Level	Level's Score
A	1	LA_1	0.875
		LA_2	0.125
B	0,0827	LB_1	0.25
		LB_2	0.75

We can see from Table 5 that level LA_1 and LB_2 are not dominated by other levels in their related attributes so that alternatives consists of level LA_1 and LB_2 should be selected as the best alternatives without bothering about the weights.

Table 6 Result of alternatives score for scenario 1.

No.	A	B	Score
1	LA_1	LB_1	1.027565
2	LA_1	LB_2	1.082694
3	LA_2	LB_1	0.170422
4	LA_2	LB_2	0.225551

Using CALAHP, we obtained the alternative number 2 which consists of level LA_1 and LB_2 as the best alternative (Table 6). So that we can assure that CALAHP can recognize nondominated solution.

4.2 Scenario 2

In this scenario, respondents have big differences in weights, but have agreement in attribute's level preferences. Scenario 2 tests model ability in dealing with different opinions about weights among respondents. Data for this scenario can be seen in appendix.

Table 7 Result of alternatives score of CALAHP and AHP's way for scenario 2.

No.	**Attribute**		***CALAHP***				***AHP***			
			Respondent			**Aggregate**	**Respondent**			**Aggregate**
	A	**B**	**1**	**2**	**3**		**1**	**2**	**3**	
1	LA_1	LB_1	1.167	1.011	0.128	1.228	0.583	0.829	0.157	0.527
2	LA_1	LB_2	1.5	1.022	1.017	1.863	0.75	0.879	0.877	0.791
3	LA_2	LB_1	0.5	0.122	0.12	0.493	0.25	0.129	0.123	0.209
4	LA_2	LB_2	0.833	0.133	1.008	1.128	0.417	0.171	0.843	0.472

Scores resulted by CALAHP are more dispersed than AHP's (Table 7). So we can see that CALAHP is more sensitive than AHP. This would strengthen the effects of respondents' preferences.

Aggregate ranks are the same for both methods. Number of agreements is 4 for respondent 1, 4 for respondent 2, and 2 for respondent 3. Total number of agreements is 10. This result still has 2 conflicts, but it considered as good enough with the different opinions of weights among respondents.

4.3 Scenario 3

In this scenario, model faces a situation where respondents have different opinions about attribute level scores, but have same preferences in weights. This situation is intended to tests the model ability to manage conflicts. The data used for scenario 3 can be seen in appendix.

Table 8. Result of alternatives score of CALAHP and AHP's way for scenario 3.

No.	**Atribut**		***CALAHP***				***AHP***			
			Respondent			**Aggregate**	**Respondent**			**Aggregate**
	A	**B**	**1**	**2**	**3**		**1**	**2**	**3**	
1	LA_1	LB_1	1.082	0.232	0.23	0.665	0.815	0.229	0.262	0.427
2	LA_1	LB_2	0.207	1.09	1.118	1.162	0.296	0.604	0.862	0.638
3	LA_2	LB_1	1.041	0.322	0.151	0.615	0.704	0.396	0.138	0.362
4	LA_2	LB_2	0.166	1.179	1.039	1.113	0.182	0.771	0.738	0.573

Aggregated preferences are relatively different from individual preferences. Number of agreements is 0 for respondent 1, 0 for respondent 2, and 4 for respondent 4. Total number of agreements is 4.

Respondent 3 whose preference is the same with aggregate's, gave extreme evaluation to the levels. So that, when weights are relatively the same and levels' scores are very different, aggregate score would be determined by respondent giving extreme evaluation.

4.4 Scenario 4

In this scenario, model faces situation where there is a dominant attribute, while the rest are relatively equal. This scenario tests model's accuration in identifying a small difference in attribute's weights.

Tabel 9 Result of alternatives score of CALAHP and AHP's way for scenario 4.

No.	A	B	C	Score of *CALAHP*	Score of *AHP*	Rank
1	LA_1	LB_1	LC_1	1.107862	0.822999	3
2	LA_1	LB_1	LC_2	1.072599	0.791799	4
3	LA_1	LB_2	LC_1	1.145199	0.855447	1
4	LA_1	LB_2	LC_2	1.109936	0.824247	2
5	LA_2	LB_1	LC_1	0.218973	0.175753	7
6	LA_2	LB_1	LC_2	0.183711	0.144553	8
7	LA_2	LB_2	LC_1	0.25631	0.208201	5
8	LA_2	LB_2	LC_2	0.221047	0.177001	6

CALAHP and AHP produce a similar rank (Table 9). There are differences in the scores of each method. CALAHP produces maximum score 1.145 and minimum score 0.184, while AHP produces maximum score 0.855 and minimum score 0.144. Range of CALAHP are wider than AHP's. With wider range, it can be concluded that CALAHP can sensitively recognize a small difference among alternatives.

4.5 Scenario 5

In this scenario, there is a dominant attribute level, while the others are relatively equal. There is also a dominant attribute weight, so that the model will face a very small differences.

Table 10 Result of alternatives score of CALAHP and AHP for scenario 5 (*continues*).

No.	Atribut			CALAHP		AHP	
	A	B	C	Score	Rank	Score	Rank
1	LA_1	LB_1	LC_1	1.094394	5	0.95258	5
2	LA_1	LB_1	LC_2	1.114828	1	0.98378	1
3	LA_1	LB_1	LC_3	1.104611	2	0.96818	2
4	LA_1	LB_2	LC_1	1.078336	9	0.92824	9
5	LA_1	LB_2	LC_2	1.098771	4	0.95944	4
6	LA_1	LB_2	LC_3	1.088554	7	0.94384	7
7	LA_1	LB_3	LC_1	1.083689	8	0.93635	8
8	LA_1	LB_3	LC_2	1.104123	3	0.96755	3
9	LA_1	LB_3	LC_3	1.093906	6	0.95195	6
10	LA_2	LB_1	LC_1	0.186987	23	0.21843	23
11	LA_2	LB_1	LC_2	0.207421	19	0.24963	17

No.	Atribut			CALAHP		AHP	
	A	B	C	Score	Rank	Score	Rank
12	LA_2	LB_1	LC_3	0.197204	20	0.23403	20
13	LA_2	LB_2	LC_1	0.170929	27	0.1941	27
14	LA_2	LB_2	LC_2	0.191363	22	0.2253	22
15	LA_2	LB_2	LC_3	0.181146	25	0.2097	25
16	LA_2	LB_3	LC_1	0.176282	26	0.20221	26
17	LA_2	LB_3	LC_2	0.196716	21	0.23341	21
18	LA_2	LB_3	LC_3	0.186499	24	0.21781	24
19	LA_3	LB_1	LC_1	0.242542	14	0.26338	14
20	LA_3	LB_1	LC_2	0.262977	10	0.29458	10
21	LA_3	LB_1	LC_3	0.25276	11	0.27898	11
22	LA_3	LB_2	LC_1	0.226485	18	0.23904	19
23	LA_3	LB_2	LC_2	0.246919	13	0.27024	13
24	LA_3	LB_2	LC_3	0.236702	16	0.25464	16
25	LA_3	LB_3	LC_1	0.231837	17	0.24716	18
26	LA_3	LB_3	LC_2	0.252271	12	0.27836	12
27	LA_3	LB_3	LC_3	0.242054	15	0.26276	15

CALAHP's alternative scores have wider range than AHP's (Table 10). Maximum score of CALAHP is 1.115 and the minimum is 0.171. While maximum score of AHP is 0.984 and the minimum is 0.194. Ranks resulted by each method are relatively the same, except for the rank 17, 18, and 19. This may be caused by different values of weight.

LA_2 and LA_3 have a very small differences. If we compare the score of alternatives consist of LA_2 and LA_3 while the other levels are the same, then we can see that CALAHP can recognize a very small differences between those alternatives. This can be seen in the score of alternative 10 and 19, 11 and 20, and so on.

5. Conclusion

From the discussion above, it is concluded that:

1. CALAHP can be used to rank *all* possible product concept alternative.
2. Compared to AHP and conjoint analysis, CALAHP has advantages as follows:
    - Using non additive weight, that is informational weight gained from attribute's level evaluation.
    - CALAHP produces continuous function of attribute's level score for level presented by real number (not ordinal levels).
    - Compared to AHP, CALAHP needs less questions to be answered.
    - Alternative scores produced by CALAHP are more dispersed than AHP's. This indicates that CALAHP is more subtle and sensitive than AHP.
    - CALAHP supports subattributes. This is not facilitated by conjoint analysis.
    - In case study, CALAHP has better prediction ability than conjoint analysis, shown by hit-rate and NAC.
3. CALAHP can recognize non dominated solution.

4. Based on the hypothetical data used in this research, for groups, CALAHP produces relatively same ranks as AHP.
5. Based on scenarios developed in this research, in the situation with greater different opinions of weights while the preferences of attribute's level are relatively the same, CALAHP can still produce good NAC. On the other hand, in the situation with greater different opinions of attribute's level, CALAHP produced less NAC.

Some recommendations for future research:

1. It would be better if data processing are conducted separately based on respondent segment generated by statistical methods, so that conflicts can be avoided/minimized.
2. Internet can be used for CALAHP implementation by building internet based model so that customers would be easier to be reached.
3. CALAHP is developed as a deterministic model. Further research can be conducted by considering uncertainty factors using statistical calculation and considering vague judgment/evaluation using fuzzy theory.

6. Appendices

Appendix A: Data for Scenario 2

Weights using CALAHP and AHP.

Atribut	***CALAHP***				***AHP***			
	Respondent			**Aggregate**	**Respondent**			**Aggregate**
	1	**2**	**3**		**1**	**2**	**3**	
A	1	1	0.017	0.672	0.667	0.875	0.1	0.54722
B	0.5	0.022	1	0.507	0.333	0.125	0.9	0.45278

Attribute level scores.

Level	**Respondent**			**Aggregate**
	1	**2**	**3**	
LA_1	1	1	1	1
LA_2	0.33333	0.11111	0.5	0.26457
LB_1	0.33333	0.5	0.11111	0.26457
LB_2	1	1	1	1

Appendix B: Data for Scenario 3

Weights using CALAHP and AHP.

Atribut	***CALAHP***				***AHP***			
	Respondent			**Aggregate**	**Respondent**			**Aggregate**
	1	**2**	**3**		**1**	**2**	**3**	
A	0.082	0.179	0.118	0.12657	0.333	0.5	0.25	0.36111
B	1	1	1	1	0.667	0.5	0.75	0.63889

Attribute level scores.

Level	Respondent			Aggregate
	1	2	3	
LA_1	1	0.5	1	1
LA_2	0.5	1	0.33333	0.69336
LB_1	1	0.14286	0.11111	0.50263
LB_2	0.125	1	1	1

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